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APPLICATION OF CONTROL THEORY TO THE INVESTIGATION OF ROLL MOTION EFFECTS ON PILOT CONTROL BEHAVIOR

A. M. Junker
6570th Aerospace Medical Research Laboratory
Wright-Patterson Air Force Base, Ohio 45433

W. H. Levison
Bolt Beranek and Newman, Inc.
50 Moulton Street
Cambridge, Massachusetts 02138

Abstract

The application of manual control theory to the investigation of the effects of motion cues on pilot control behavior is presented. Experiments and modeling approaches which have led to the development of a predictive motion sensitive optimal-control pilot-vehicle model for roll axis motion cues are described.

1. Introduction

Emphasis on expanding the use of ground based simulators has caused the Air Force to take a more critical look at the usefulness of moving base simulators. This has resulted in the realization that the technology necessary to specify adequately motion cue requirements is not available and that the effects of motion cues on pilot control behavior, as presently available on moving base simulators, are not clearly understood at this time.

At the Aerospace Medical Research Laboratory (AMRL) we believe that some of these deficiencies can best be minimized through the application of Manual Control technology. By making use of a predictive pilot model which is sensitive to motion environments, the effects of simulator motion on the pilot can be mathematically described. Having a quantitative measure of the motion cue effects, better design schemes can be implemented.

Considerable research has been performed in the area of manual control and a broad foundation has been built upon which we can now develop the needed technology. As stated in reference [18] there are two basic types of pilot models available; describing function models and state space models. The first type, which is formulated in the frequency domain, originated with classical control theory [19]. The second type of pilot model, which is formulated in the time domain, was developed from modern control and estimation theory [9].

When we began our research program to include the effects of motion environments in a predictive pilot model neither modeling approach could account for motion cues adequately. Although a number of experimental studies have been conducted to determine the effects of motion cues on pilot response behavior [1-5], a generalized model has not been developed and tested. Rather, the conclusions reached in these studies have been restricted to the context of the experiments yielding the data.

Perhaps the most comprehensive study of the effects of motion cues on tracking performance was conducted by Shirley [3]. He explored overall system performance and pilot response behavior in a series of tasks that included a wide range of vehicle dynamics. Most of his results conformed to the following set of rules; the human operator uses motion to generate additional lead at high frequencies, greatest percentage reduction in RMS error scores with motion is achieved for systems that respond to inputs above 3 rad/sec, and motion is used to greatest advantage in marginally stable systems. Stapleford et al. [2] also found that high-frequency phase lag decreased and gain crossover frequency increased when motion cues were present; furthermore, these effects generally decreased as the vehicle dynamics increased in difficulty. In contradiction to Shirley, however, they found that, on the average, the effects of motion cues on error score increased for increasing vehicle difficulty. In addition, other than the pitch axis motion experiment performed by van Gool and Mooij [5], the work done in this area has principally been for compensatory systems with the motion cues resulting from vehicle disturbance inputs. At AMRL we were also interested in quantifying the effects of motion cues on pilot control behavior for situations in which the motion cues resulted from pilot control inputs due to target following as encountered in air-to-air combat situations.

To investigate the effects of motion cues on pilot control behavior we built a simple closed loop moving base simulator. We chose motion about the roll axis because roll control as an inner loop is essential in flying an airplane and pilots normally experience the largest velocities and accelerations about this axis. The Roll Axis Tracking Simulator (RATS) was developed initially so that target following motion experiments could be performed. A series of experiments were run to determine if the presence of motion cues would affect tracking performance, and if so how would the motion cues modify pilot control behavior [6,7]. From these experiments we found that motion cues could have both a positive and negative effect on tracking performance depending on the vehicle dynamics being controlled and the type of motion cues provided. At this time we also realized that because the effect of motion simulation on tracking performance is highly dependent on the details of the tracking task, generalization of the type reviewed above [1-5] and our experiments could not be reliably extended beyond situations similar to those studied experimentally. An alternative philosophy has been suggested and partially explored: Namely, to account for the pilot's use of motion cues by including additional sensory feedback paths in a pilot model [1]. Given a model structure that allows one to predict the influence of these feedbacks on pilot response as a function of task parameters, one may then extend experimental results to a variety of control situations. At the time, the optimal-control pilot-vehicle model as developed by Bolt Beranek and Newman (BBN) [8-11] seemed to possess this structure. Therefore we provided data to BBN to explore the model's capability of accounting for the effects of motion cues on pilot control behavior by including additional sensory feedback paths in the model. The results of this effort [12] were highly successful.

At this same time we wanted to investigate the possibility of providing the equivalent of motion cue information to the pilot through means of a peripheral display system. We had subjects track statically on the RATS with vehicle roll rate driving the peripheral display. Analysis of the tracking data indicated that it was possible to achieve similar performance improvements with the peripheral display as with motion cues [7].

From our modeling efforts we had a pilot-model which could account for the effects of motion cues resulting from commanded inputs due to target following on the RATS. Since this was a predictive pilot model which had accounted for motion effects by additional sensory feedback loops, it was hoped that the model could also be used to account for motion cues resulting from vehicle disturbances and for different vehicle dynamics. To test this and to extend our data base of motion related human tracking, we developed a multi-axis tracking simulator (MATS) and performed disturbance tracking as well as target tracking experiments on this simulator. Prior to performing the experiment we used the pilot-vehicle model as an aid in the experimental design and to predict the experimental results [13]. Experimental data was then collected and further adjustments were made to the pilot model [14]. The results of this effort were highly successful yielding a predictive pilot-vehicle model sensitive to the presence of motion cues.

The above is a brief sketch of our research program which has led to a better understanding of the way in which man uses motion cues to aid his performance and to the development of a predictive motion sensitive pilot-vehicle model. In the remainder of this paper we will describe in some detail the experiments and modeling efforts which have enabled us to get to this point.

2. Experiment No. 1

This experiment was designed and performed for two reasons: first, to provide a data base of human operator tracking, with the presence of motion cues, for the situation in which motion had a positive affect on tracking performance and second, to understand the effects of linear and angular acceleration motion cues on tracking behavior.

While tracking in a moving base simulator that has roll motion, the human controller is exposed to both angular acceleration or velocity information and linear acceleration information of the simulator he is controlling. For modeling purposes it is desirable to understand the effects of the two types of motion separately. Due to changing alignment of the gravity vector while tracking in the RATS a human controller is provided with continuous information about his orientation relative to the vertical through proprioceptor cues and vestibular otolith stimulation. This alters the visual compensatory tracking task to one of a pursuit type task resulting in a possible improvement in performance. But a multiloop modeling approach to previous RATS data [15] suggested that the angular acceleration component was the principal source of information used for tracking performance improvement. Stapleford et al. [2] also concluded that the improvement in performance is primarily due to angular rate feedback via the semicircular canals. The desire to better clarify this situation by measuring the effects of each type of motion separately led us to devise an experiment in which the equivalent of angular velocity cues was provided to the human controller without the presence of linear acceleration information. This was accomplished through the use of a peripheral visual display. The impetus for using this technique came from the work of Ener [16].

For this experiment we used the RATS which consists of a roll axis drive system, seat, visual display and side mounted force stick for motion control. The rotating system dynamics were identified and simulated on a hybrid computer. A generalized block diagram of the resulting system is shown in Fig. 1. For this experiment $\Phi_{DISTURBANCE}$ was set to zero. The simulator could be operated in two modes: motion and static. In the motion mode the force stick output went to the plant dynamics as a velocity command. In this mode, the

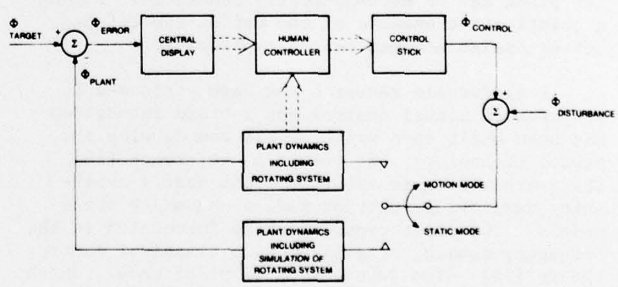

Fig. 1. Block Diagram of Target and Disturbance Tracking Tasks.

inputs to the human operator were motion cues and visual display. For the static mode, the stick output drove only the simulated plant dynamics. The plant dynamics given in equation 1 were used because we knew from previous work [6] that motion cues would have a beneficial effect on performance for these dynamics.

$$\text{PLANT DYNAMICS} = \frac{42}{s^2(s+0.5)(5+6)} \tag{1}$$

The task was to follow another aircraft in the roll axis. The target aircraft was driven by a second order noise process, consisting of 12 sine waves, with break point at 0.5 rad/sec and an RMS roll angle of 40°. The method used to select the 12 frequencies and amplitudes and generate the target signal was taken from Levison [17].

The RATS was run in the static mode for that protion of the study in which the peripheral display was used. The peripheral display was presented to the human controller on two 21-inch television monitors placed on opposite sides of the RATS (Fig. 2).

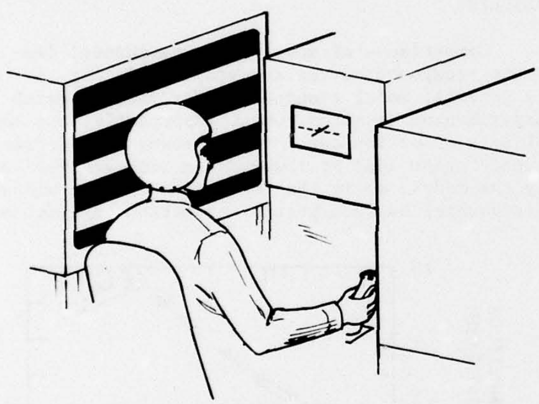

Fig. 2. Placement of Peripheral and Central Displays.

The central display used for all three conditions (static, with motion or with peripheral display) is shown in Fig. 3. The target aircraft, represented by the solid lines, rotated about the x-axis. Thus the visual tracking task was to null out the difference between the target and the controlled vehicle represented by the dashed line.

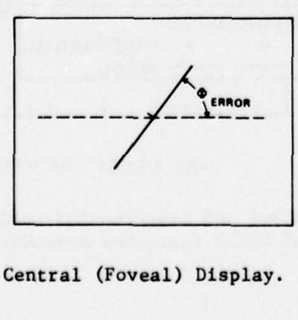

Fig. 3. Central (Foveal) Display.

The peripheral display presented plant roll rate information in the form of vertical movement of alternating black and white horizontal lines. The voltage representing plant roll rate was scaled and connected to the peripheral display circuitry. The circuitry was connected such that the displays of the two sets moved in opposite directions. Therefore a static plant roll rate signal resulted in horizontal line movement equal in magnitude and direction of the linear velocity stationary objects located in the position of the peripheral displays would appear to have if the RATS were to actually rotate.

Four subjects were used in the experiment. Each subject performed four tracking runs per day. The duration of each run was 165 sec and the order of runs (one for each experimental condition) was randomized. RMS error scores were computed after each run. Once the error scores indicated that the subject had "learned" the tracking task for a given experimental condition, time histories were recorded for subsequent use in analyzing subject control strategy. The sampled data recorded was converted to desired performance measures using a frequency analysis digital computer program modeled after one written by Levison [17].

RESULTS

The results of this experiment which are highlighted below are presented in greater detail in ref. [7]. The daily tracking scores for each subject for each experimental condition were combined to yield group means and standard deviations. The results of the last four days of tracking (after asymptotic levels were reached) are plotted in Fig. 4. As was expected a significant improvement in performance with motion cues was measured. In addition the scores signify that nearly identical improvements were achieved with the peripheral display.

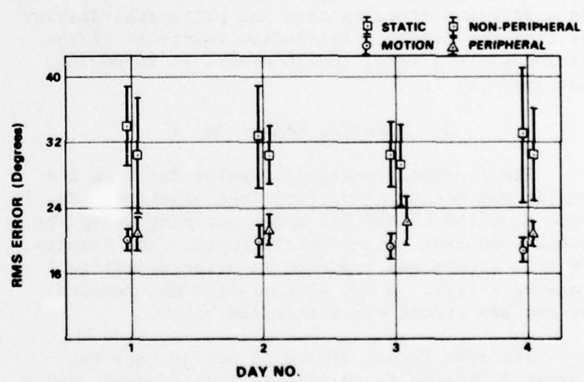

Fig. 4. Combined Error Scores, Last Four Days.

To see how subjects performance was improved, describing functions were computed and evaluated. Group averaged subject describing function means for the motion, peripheral and static conditions have been plotted in Fig. 5. The significant effects are improvements in low frequency phase lead with motion. This same trend was measured for the peripheral display condition as well.

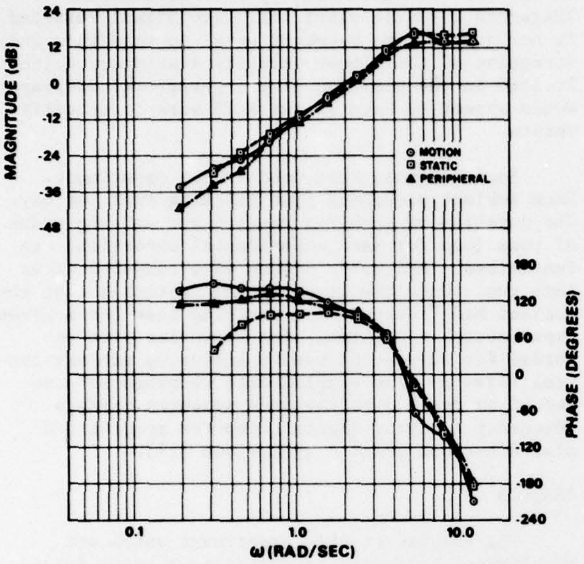

Fig. 5. Combined Man Describing Functions.

From these results we conclude that the peripheral display information has the same effect on the human operator control strategy as motion cues; namely, that he uses this plant rate information to improve his low frequency phase lead capabilities. It should also be added that the describing function phase values do indicate a greater phase lead improvement for the motion case over the peripheral case. This suggests that either the motion is a stronger stimulus than the peripheral display or that the linear acceleration component of the motion plays a role, though minor, in improving performance.

3. Modeling Effort No. 1

The frequency analysis results for both the static and motion conditions from experiment No. 1 were supplied to BBN for model matching using the optimal-control pilot-vehicle model. The results of this effort are reported in great detail in reference [12]. A few of the principal results of the BBN effort are summarized below.

The significant effect of motion cues for target following is to improve low-frequency phase lead. Without motion cues present the human operator describing function exhibits what has been called low-frequency "phase droop". Therefore, the first thing done to the optimal-control model was to modify it to account for this phase droop. This was accomplished by modifying it to allow a different treatment of motor related pilot "noise". Specifically, the concept of "pseudo motor noise" was implemented to provide a model parameter related more directly to uncertainties about the control system as well as uncertainties about the pilot's control input. In addition, changes were made so that noise was injected on control rate as suggested in a previous study [10].

The focus of the modeling effort was to represent the effects of motion primarily by appropriate definition of the sensory variables assumed to be available to the pilot. Thus, static-mode tracking was modeled with a two-element "display" vector consisting of tracking error and error rate. In the case of motion tracking, the display vector was augmented to include quantities that would be provided by the pilot's motion-sensing capabilities; specifically, plant position (i.e., roll angle), plant rate, and plant acceleration.

With the optimal-control model modified, the data from experiment No. 1 was used to identify the model parameters. An iterative procedure was followed to arrive at a set of pilot-related parameter values that would explain the maximum amount of data with the minimum variation in parameters.

RESULTS

Comparisons of model and experimental frequency-response curves are provided in Fig. 6. In general, model response curves closely match experimental measures. Most importantly, the major effects of motion cues--the increase in low-frequency phase lead at low-frequencies--are mimicked by the model, as is the consistency of the midband frequencies between static and motion conditions.

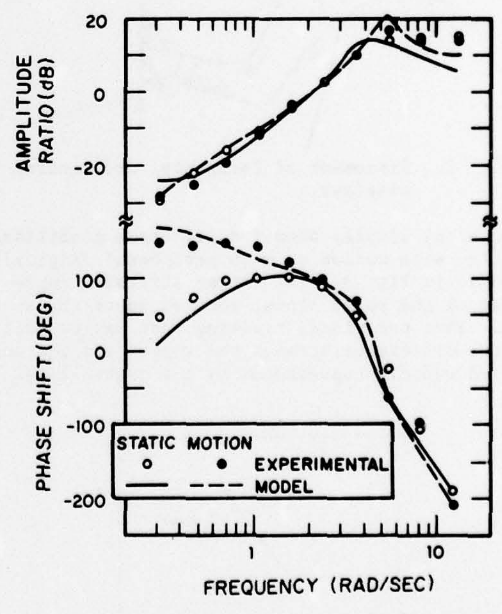

Fig. 6. Model and Experimental Data Comparison of Pilot Frequency Response.

4. Experiment No. 2

Since the optimal-control pilot-vehicle model has predictive capabilities, the next step was to ascertain how well it could predict pilot performance under different experimental conditions. A Multi-Axis Tracking Simulator (MATS) was used as the controlled vehicle for this experiment. Only the roll axis motion capabilities of the MATS were used. The simulator consisted of a single seat cockpit with a television monitor display and side-mounted force stick for vehicle control. The display of Fig. 3 was used. The roll axis system dynamics were identified and simulated on a hybrid computer. To test the capabilities of the optimal-control pilot-vehicle model and be able to compare our results with other motion cue experiments, we investigated the effects of two types of motion cues in this experiment. The first was target following as in experiment no. 1. The other was for motion cues resulting from the controlled vehicle being driven by disturbances. Both conditions were investigated with and without motion, making a total of four experimental conditions. The block **diagram** in Fig. 1 shows all conditions. For target following the disturbance input(ϕDISTURBANCE) was set to zero and for the disturbance condition the target input (ϕTARGET) was set to zero. The plant dynamics used for all conditions are given in equation 2.

$$\text{PLANT DYNAMICS} = \frac{K}{s(s+5)(s+20)} \qquad (2)$$

With the vehicle to be controlled identified, the next step was to select task parameters for the experiment. The following design goals and constraints were considered; face validity, motion cue utilization, wide bandwidth response, and simulator motion limitations. Experimental parameters that we could adjust to meet these goals consisted of (1) RMS amplitude and spectral shape of the tracking input, (2) control gain and, (3) performance criterion. The input amplitude was adjusted to induce vehicle response of the desired magnitude, and the control gain was adjusted to allow such response to be achieved with comfortable control forces. A second order noise process was considered for the tracking input and the critical frequency of the input spectrum was chosen to achieve the desired balance between measurement bandwidth and tracking difficulty. To keep RMS response rate and acceleration well below the physical limitations of the rotating simulator, as well as to encourage the test subjects to respond in a smooth manner, a performance criterion was defined as the weighted sum of mean-squared tracking error and mean-squared vehicle acceleration. That is,

$$C = \sigma^2_{\phi_{ERROR}} + W\,\sigma^2_{\ddot{\phi}_{PLANT}} \qquad (3)$$

where C is the total "cost", $\sigma^2_{\phi_{ERROR}}$ the variance of the tracking error, and $\sigma^2_{\ddot{\phi}_{PLANT}}$ the variance of the acceleration of the vehicle or simulated vehicle in the absence of motion cues.

The immediate effect of introducting a penalty for vehicle acceleration was to limit the gain of the subject's response; the larger the weighting W, the lower the pilot gain. Pilot gain directly influenced overall man'machine system bandwidth, which in turn influenced roll rate and roll accelerations achieved during tracking.

Task parameters were selected in the following way. An initial set of parameters was chosen based on knowledge gained from previous experimental studies, and predictions of pilot-vehicle performance were obtained with the pilot-vehicle model. Task parameters were readjusted in an attempt to better meet the experimental constraints, and the system was reanalyzed. We iterated on this procedure until satisfied with the expected outcome of the experiment, as predicted by the optimal-control model. As a result of this iterative design process the following task parameters were selected. The force stick gain was adjusted to produce 10 degrees/second vehicle roll rate for one pound of force measured at thumb height on the control grip and the cost weighting W (equation 3) was set to 0.1. In addition, both the target and disturbance inputs were constructed from 13 sinusoids whose amplitudes were selected to simulate a second order noise process with bandwidths of 1.0 rad/sec for the target input and 2.0 rad/sec for the disturbance input. Input amplitude was adjusted to provide an RMS target input of 10 degrees and an RMS disturbance input of 14 deg/sec. With task parameters selected, the model was used to predict pilot-vehicle performance values which were saved for later comparison with experimental results. Six subjects were used for the experiment. One of the subjects was a licensed pilot and another a student pilot.

RESULTS

Once subject training had been accomplished, data was collected for eight days for all subjects. Training was considered completed when subject performance as measured by total cost C for all conditions had reached asymptotic levels.

From the collected data various system parameter values were computed and averaged together across days and subjects. The experimental values include the mean and standard deviation resulting from averaging together the six subjects' results. Shown in Fig. 7 is a graphical comparison of predicted and experimental results for total cost (PERFORMANCE SCORE) and pilot input (RMS CONTROL FORCE). Experimental conditions are indicated on the abscissa of each graph; C indicates the Command (target following) condition, D indicates the Disturbance condition, M is for Motion and S for Static. These results indicate that the model could predict performance results quite accurately. The same trends were observed for other system parameters as reported in reference [13].

As stated earlier the motion sensitive aspects of the model were developed for experimental condtions different from those investigated in this experiment and a different simulator with narrower bandwidth vehicle dynamics; experiment No. 1. These facts further emphasize the usefulness of the predictive capabilities of the model.

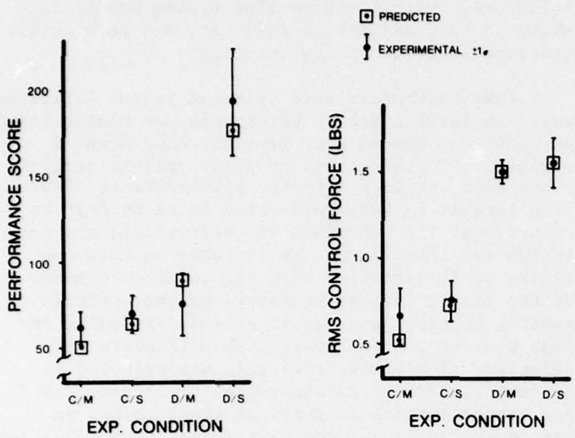

Fig. 7. Comparison Between Model Predictions and Experimental Results for Performance and Control Force.

From the time history data frequency-response measures were computed. The results of the six subjects were averaged together. The average frequency-response measures presented in Fig. 8 show that motion-cue effects were qualitatively different for the two tasks. The two measures shown in the figure are amplitude ratio (i.e. pilot gain) and pilot phase shift. The major influence of the motion cues in the target task was to induce a substantial phase lead at low frequencies. In the disturbance task, however, motion cues allowed the subjects to convert a high-frequency phase lag into a substantial phase lead and to increase amplitude ratio at low and mid frequencies. The effects of motion cues observed in the disturbance-regulation task agree with the effects reported by other researchers [2,3] who found that moving-base simulation allowed the pilot to reduce high frequency phase lag and to increase gain-crossover frequency and thereby, in many cases, lower his error score. The data from this experiment is analyzed in greater detail in reference [14].

5. Modeling Effort No. 2

Data resulting from experiment No. 2 was used to make further refinements to the motion sensitive optimal-control pilot-vehicle model. The results of this modeling effort are reported in great detail in reference [14]. The revised optimal-control pilot-vehicle model developed in a preceding phase of this study was applied to the results of the experiment described above.

The treatment of motion cues was similar to that of the preceding modeling effort in that presence or absence of motion cues was represented by an appropriate definition of the sensory variables assumed to be available to the pilot. A three-element "display vector" consisting of tracking error, error rate, and (in one instance) error acceleration was used to model static-mode tracking. To model pilot response in moving-base tasks, we simply expanded this display vector to include position, rate, acceleration, and acceleration-rate of the vehicle; no other model parameters were changed to account for motion-static difference.

The scheme for identifying model parameters was similar to that described in [12]. Parameter values were sought that would simultaneously provide a good match to performance scores, describing function, and remnant ratio. As in the preceding modeling effort, the primary goal of model analysis was to determine a straightforward and reliable procedure for predicting the effects of motion cues in a variety of control tasks. Therefore, we attempted to account for performance on all four tasks with the fewest variations in parameter values. Variations were made in only those parameters that could reasonably be expected to relate to the kind and quality of information provided to the pilot. Attentional parameters were the only model parameters that were varied across experimental conditions; all other parameter values were held fixed. The results of this modeling effort are shown in Fig. 8. Model outputs agreed quite well with experimental frequency-response measures, and major trends in the data were predicted. Specifically, inclusion of motion-related sensory information caused the model to predict an increase in low-frequency phase shift for the target task. For the disturbance task, the model correctly predicted large increases in low-frequency gain and high-frequency phase lead.

It is worthwhile to re-emphasize that the effects of motion cues have been accounted for solely by changes in model parameters related to the information availability and quality; other parameters have been kept fixed for the four experimental conditions.

6. Conclusions

Some of the conclusions that can be made as a result of the experiments and modeling effects performed in this research effort are summarized below.

The effects of motion cues on task performance and pilot response behavior are strongly dependent on the structure of the tracking task. The major effect of motion cues in a target-following task is to allow the pilot to generate low-frequency phase lead; in a disturbance-regulation task, the main effects are more phase lead (alternatively, less phase lag) at high frequencies accompanied by an increase in gain-crossover frequency.

Because of the strong interaction between motion-cue effects and task structure, a pilot-vehicle model is required to extrapolate the results from one task to the next.

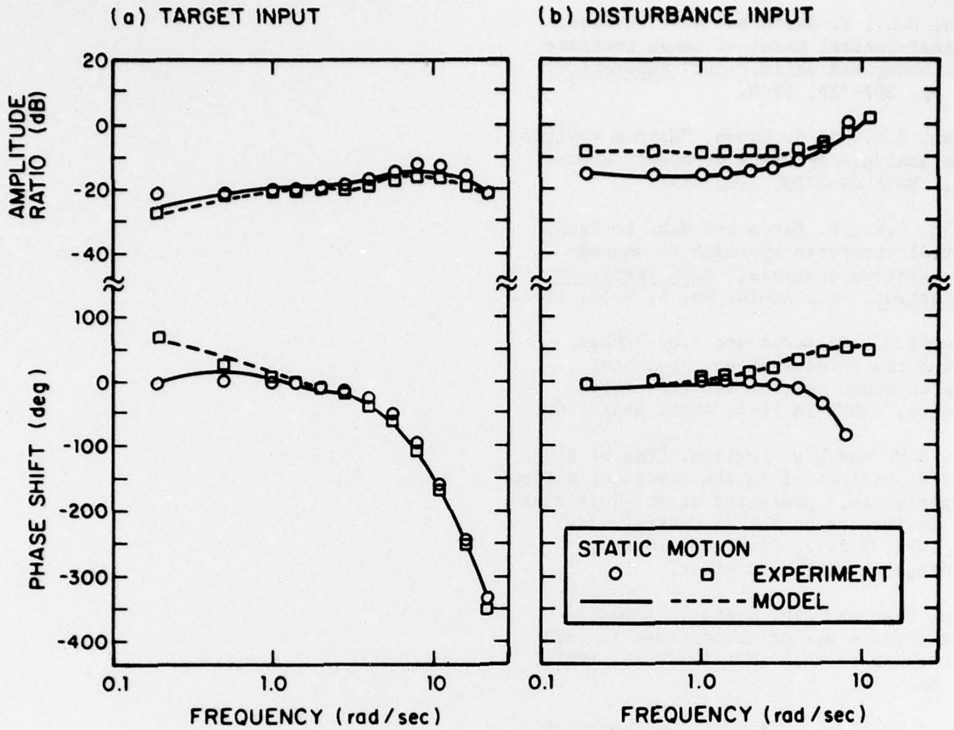

Fig. 8. Comparison of Model and Experimental Frequency Response.

The "optimal-control" model for pilot-vehicle systems provides a task-independent framework for accounting for the pilot's use of motion cues. Specifically, the availability of motion cues is modeled by augmenting the set of assumed perceptual variables to include position, rate, acceleration, and acceleration rate of the moving vehicle.

As a result of our modeling effort we now have a predictive motion sensitive pilot-vehicle model for the roll axis. We are presently making use of this model and the knowledge gained from our experiments and others to investigate such things as visual-motion cue mismatch and motion simulator washout drive algorithms. By utilizing a manual control technological approach we plan to quantify the above effects on pilot control behavior and correlate the control behavior with subjective responses.

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